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Digital Transformation of Concrete Technology—A Review

Yaser Gamil and Andrzej Cwirzen*

Building Materials, Department of Civil, Environmental and Natural Resources Engineering, Luleå University of Technology, Luleå, Sweden

Digital transformation of concrete technology is one of the current "hot topics" tackled by both academia and industry. The final goal is to fully integrate the already existing advanced concrete technologies with novel sensors, virtual reality, or Internet of things to create self-learning and highly automated platforms controlling design, production, and long-term usage and maintenance of concrete and concrete structures. The digital transformation should ultimately enhance sustainability, elongate service life, and increase technological and cost efficiencies. This review article focuses on up-to-date developments. It explores current pathways and directions seen in research and industrial practices. It indicates benefits, challenges, and possible opportunities related to the digital transformation of concrete technology.

Keywords: digital transformation, concrete properties, concrete technology, sustainability, advanced technology, monitoring

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****Correspondence:***
Yaser Gamil
yaser.gamil@ltu.se

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INTRODUCTION

Digitization refers to transfer of data stored in traditional documents to binary forms, while digital transformation is defined as a process of changing existing methods and models by utilizing latest IT technologies to produce real-time information for fast decision making (Parusheva, 2019; Zeltser et al., 2019; Daniotti et al., 2020; Papadonikolaki et al., 2020). For cement and concrete industries, it facilitates the process of data acquisition, their analysis, and utilization (Walther, 2018). Production of concrete starts with material characterization, mix design, and actual mixing followed by its transportation to a building site (Tomek, 2017). A significant amount of data created can be digitalized and used to control that process (Rasmussen and Beliatis, 2019). The digital transformation is expected to produce a more efficient process, improving the working environment and sustainability of concrete products (Phang et al., 2020). However, a number of challenges still need to be addressed, for example, methods for reliable prediction of early-age properties, modeling of hardening processes, and development of strength or durability (Wangler et al., 2019).

Concrete structures can be cast directly on a building site or prefabricated in advanced in a factory. The cast-on-site technique is preferable for monolithic, large-size structures including foundations, beams, columns, slabs, retaining walls, tunnels, and bridges (Liu et al., 2020). Concrete is transported from a ready-mix plant to the building site and then placed using pumps or dumpers. In the case of precast technology, concrete elements are cast in production halls and after achieving sufficient strength, transported to the building site. The cast-in-place technology offers more flexibility and adaptability (Simonsson and Emborg, 2009). Weakness includes sensitivity to weather, that is, extreme temperatures, wind, and precipitation. The current industrialization degree of concrete technology is relatively high, but it still requires several improvements in the quality of work, optimization of the process, and enhanced sustainability. It is foreseen that there is a possibility to expedite the process using the latest digitalization techniques and technological advancements (Wangler et al., 2016). Self-compacting concrete (SCC) is increasingly used, especially for the cast-in-place technique, which, due to the exclusion of vibration, offers a faster construction process and better working conditions (Ouchi, 2000). The main advantages include high casting rate and passability in congested reinforcement (De Schutter et al., 2008). The main challenge while using SCC is a need to use a new casting technology (Ferrara et al., 2007).

The digitalization process starts by merging material properties and construction techniques into an integrated digital environment. It includes digitalizing of fresh concrete properties, hardening processes, strength development, and durability using data collected from either manual measurements or installed sensors. The integration of measured parameters and digital technology enables to enhance the quality of concrete. However, it requires a strengthened collaboration between research and industry (Courard et al., 2014). Data collected from sensors can be integrated into a monitoring system, building information models, and controlling software. This process is expected to introduce a safer and error-free process and improve the productivity. The site supervisor has real-time access to data, which should facilitate the decision-making process related to, for example, the optimum casting speed, safe demolding time, or the required curing routine.

Research has been on going in the field of digital concrete, which refers to the digital fabrication of concrete, for example, 3D printing and robotics in digital fabrication (Wangler et al., 2016; Wangler et al., 2019; Van Damme, 2020). Those studies have explored the methods of fabrication and construction. The basic properties, mix design parameters, and their associated information need to be addressed. Commonly, these data are obtained in the laboratory, and the question remains open about the possibility of transforming the information acquisition into a digital process. This article reviews previous research dealing with digital transformation in concrete technology, and it focuses on latest developments with a special emphasis on disadvantages and limitations. It also indicates areas that need further improvements. This article is part of a project where attempts are made to develop a system that can help integrate all the available technologies into one smart decision-making system that enables engineers to foresee and expect the outcome of the mix design based on the inputs of material properties either physically or chemically related.

MATERIAL CHARACTERIZATIONS AND MIX DESIGN

Advanced technologies such as virtual reality, 3D printing, Internet of things, smart sensors, and autonomous robots and vehicles have already been used in various industries. However, the concrete industry is clearly behind due to the lack of acceptance, related cost, current regulations, and new required expertise. Concrete itself has gone a tremendous development path over the past few decades. Cement has been partially or fully replaced with several types of by-products to enhance some properties and to increase its sustainability. At the same time, casting technology has remained rather unchanged (Ferrara et al., 2007).

Concrete consists of binder, coarse and fine aggregate, water, admixtures, and various types of dry and wet additives. These materials are characterized by chemical composition, surface area, shape, texture, and amount of intermixed fine and coarse aggregates. These properties affect the mix design and behavior of concrete during mixing and casting and later determine hardened state properties and, often, also durability (Polat, 2013). The following sections will review currently used methods which are/or could be used to digitalize the properties of concrete ingredients.

Aggregates

Aggregates used in concrete include gravel, crushed stone, sand, slag, recycled concrete, and geosynthetic aggregates. They occupy up of 70–80 vol.% of concrete mix and affect most of its physical and mechanical properties. Aggregates should be clean, hard, and free of chemical and biological contaminants (Babu, 2014). Their quality and properties are quantified by several indicators, including shape, texture, air content, particle size distribution, water content, specific gravity, or density. Some of these indicators have already been successfully digitalized. For example, volume, angularity, and gradation have been determined using analysis of images obtained from video cameras. The obtained results have been in good agreement with manual measurements (Rao and Tutumluer, 2000). 3D mathematical analysis of particle shape has been successfully combined with X-ray tomography and spherical harmonics to determine particle shapes (Garboczi, 2002). Others used the same technique but supplemented it with a virtual reality modeling language. This approach enabled to obtain 3D images of aggregate particles (Erdogan et al., 2006). The surface texture has been determined using imaging techniques coupled with wavelet analysis of grey images. Unfortunately, results were strongly affected by the angularity and form of aggregates (Al-Rousan et al., 2007). The shape index and morphological features of coarse aggregates have been assessed by a digital processing approach, which established a correlation between the shape of aggregate and mechanical properties of asphalt concrete (Arasan et al., 2011). The shape of aggregates affected the required cement content, as well as the mechanical properties and durability of the produced concrete. Content of air voids in aggregates can be directly linked to the observed water demand. It has been determined by a feed-forward neural network with the error back-propagation algorithm using artificial neural networks (ANNs) and multiple linear regression with specific toolkits such as NTR2003 and WEKA (Zavrtanik et al., 2016). Digitalization of other properties, that is, water content, specific gravity, and density, appears to be still at a very early stage. A summary of research related to the digitalization of aggregate properties is shown in **Table 1**.

Cement

Selection of cement type and its amount must ensure achieving the targeted fresh and hardened state properties. The decision-making

TABLE 1 | Digitalization of aggregate properties.

Targeted properties	Technology/method	Tool(s)	References
Volume, angularity, and gradation	Image-analysis approach	Video cameras	Rao and Tutumluer (2000)
Particle shape	3D mathematical analysis of particle shape	X-ray tomography and spherical harmonics	Garboczi (2002)
Aggregate shape	3D image analysis	X-ray computed tomography and spherical harmonic analysis	Erdogan et al. (2006)
Aggregate shape and texture	Imaging techniques	Wavelet analysis of grey images	Al-Rousan et al. (2007)
Shape index and morphology	Digital image processing	ImageJ Java	Arasan et al. (2011)
Air void content in the aggregate mixture	Feed-forward neural networks with error back-propagation algorithm using ANNs and multiple linear regression	NTR2003 and WEKA toolkit	Zavrtanik et al. (2016)

TABLE 2 | Digitalization of cement properties.

Targeted properties	Method	Tool(s)	References
Cement composition	A diffuse reflectance mid-infrared Fourier-transform spectroscopy (DRIFTS)	Fourier-transform infrared (FTIR) spectroscopy	Hughes et al. (1995)
Particle size distribution	Laser diffraction and photon correlation spectroscopy (PCS)	Photocentrifuge and X-ray disc centrifuge	Bowen (2002)
Particle size	By spreading the light around the particle's contours	Laser diffraction spectrometry	Hackley (2004)
Particle shape and chemical composition	Micrometer-scale 3D shape	X-ray microcomputed tomography	Erdogan (2010)
Particle size and specific surface area	Brunauer–Emmett–Teller (BET)	Laser diffraction X-ray computed microtomography	Ferraris and Garboczi (2013)
Structural and optical properties of cement	Size and strain plot (SSP) methods	X-ray diffraction (XRD) and (FTIR) spectroscopy	Suryani et al. (2020)

process is usually strongly regulated and depends, for example, on the exposure conditions or planned service life of the structure. Potentially, it could be automated through digitalization by utilizing research data collected over the last few decades combined with regulations and practical observations. As it will be shown later, most methods used in the current practice provide digital data which could be implemented into IT platforms. For example, Hughes et al. (1995) used Fourier-transform infrared (FTIR) spectroscopy to determine the cement composition, while Hamza et al. (2017) established the impact of the cement type on the resistance of concrete to sulfate attack. Suryani et al. (2020) determined the structural and optical properties of cement with the aid of X-ray diffraction (XRD). It included crystal size, microstrain, energy deformation, and stress.

The specific surface area of cement is a crucial parameter when selecting the cement type. Larger surface enhances the hydration process (Neville and Brooks, 1987). This parameter has been determined by various techniques, for example, neutron scattering, gas sorption, small-angle scattering, nuclear magnetic resonance imaging, X-ray scattering, and mercury intrusion porosimetry (Winslow and Diamond, 1974; Olek et al., 1990; Thomas et al., 1998). Unfortunately, none is digitalized and require additional manual work to transform collected data into a usable digital format (Thomas et al., 1999). Ferraris and Garboczi (2013) measured the particle size and specific surface area by laser diffraction X-ray computed microtomography, which enabled to determine particles as small as 45 μm. Another method is laser diffraction spectrometry, which determines the particle size by spreading the light around the particle's contours (Hackley, 2004). It is able to detect particles having diameters in the range between 10 μm and 1 mm (Bowen, 2002). Erdogan (2010) used the X-ray microcomputed tomography technique incorporated with spherical harmonic analysis to determine the 3D shape of cement particles for characterizing cement, based on particle shape and chemical composition. In that case, the used spherical harmonic analysis enabled to determine the particle length, width, and thickness. The average shape of cement particles has been correlated with the volume fraction of belite and alite. A summary of digitalization of cement properties is given in **Table 2**.

Concrete Mix Design

The concrete mix design establishes the proportions and type of its constituents, that is, binder or binders, aggregates, fillers, water, chemical additives, admixtures, and possible fibers. The concrete mix design along with other factors, especially including, casting technology, curing procedure, and environmental conditions, determines the ultimate workability, strength, or durability of concrete. The concept of digitalizing the concrete mix design has been used for a relatively long time already. For example, the water-to-cement ratio has been determined using a near-field microwave technique with an open-ended rectangular waveguide probe radiating into OPC materials at 5 GHz

TABLE 3 | Digitalization of the mix design.

Targeted parameters	Technology/method	Tool(s)	References
Water-to-cement ratio and cure state	Near-field microwave techniques	Open-ended rectangular waveguide probe radiating into OPC materials at 5 GHz (G-band) and 10 GHz (X-band)	Bois et al. (1998)
High-performance concrete	ANNs	Non-linear programming	Yeh (1999)
Dosage of materials, cement grade, and the effect of admixtures	ANNs	Knowledge-acquisition system, Visual C++	Ji-Zong et al. (1999)
Coarse aggregate-to-cement (ca/c) ratio	Non-destructive testing technique	Microwave near-field reflection property analysis and open-ended rectangular waveguide probes	Bois et al. (2000)
Water-to-cement ration (w/c)	Real-time and on-site evaluation	Microwave non-destructive testing and monopole antenna probe	Mubarak et al. (2001)
Nominal and equivalent w/c ration, FA-to-binder ration, and aggregate size	ANNs	Design algorithm	Ji et al. (2006)
Water-to-cement ratio	Real-time and on-site microwave non-destructive testing	Monopole antenna probe; the probe operates with 3 GHz with a reflectometer to determine the w/c ratio	Providakis et al. (2011)
Optimizing mix design	Adaptive neural fuzzy inference systems and fuzzy inference systems	Fuzzy expert system	Neshat (2012)
OPC, water, and fine and coarse aggregates	Simplex and modified regression theories	Visual basic and computer-aided design	Onwuka (2013)
Optimizing mix design	3D printing	Laboratory-based optimization	Lediga and Kruger (2017)
Optimizing mix design	Machine learning techniques using ANNs	Quasi-Newton training direction calculated using the Broyden–Fletcher–Goldfarb–Shanno algorithm	Ziolkowski and Niedostatkiewicz (2019)

(G-band) and 10 GHz (X-band) (Bois et al., 1998). The same concept has been also applied to determine the coarse aggregate-to-cement (ca/c) ratio (Bois et al., 2000). A real-time, on-site evaluation of the water-to-cement ratio (w/c) used microwave non-destructive testing (Mubarak et al., 2001). A monopole antenna probe, operating at 3 GHz with a reflectometer, has been also used to efficiently determine the w/c ratio (Providakis et al., 2011). The concrete mix design has been also optimized by artificial neural networks (ANNs) using various input data, for example, workability or compressive strength (Ji-Zong et al., 1999; Yeh, 1999; Ji et al., 2006; Ziolkowski and Niedostatkiewicz, 2019). The method enabled estimation of dosage of materials, choice of the type of cement, and effects of chemical and mineral admixtures (Ji-Zong et al., 1999). The same concept but with different design algorithms has been used to estimate nominal and equivalent w/c ratios, fly ash (FA)-to-binder ratio, and aggregate size (Ji et al., 2006). Others used a set of concrete recipes to optimize the mix design based on maximum aggregate size, slump, fineness modulus, and compressive strength by incorporating an adaptive neural fuzzy inference system (Neshat, 2012). Recently, a machine learning algorithm has been used to optimize the mix (Ziolkowski and Niedostatkiewicz, 2019). Concrete mixes for 3D printing were designed to obtain the required extrudability, buildability, workability, and open time (Lediga and Kruger, 2017). A summary of digitalized methods and tools used in the concrete mix design is shown in **Table 3**.

CONCRETE PROPERTIES

Concrete Temperature

The temperature of fresh concrete and the ambient temperature are very important parameters while designing concrete mix composition, or planning, transporting, casting, and curing (Shoukry et al., 2011). Generally, high temperature accelerates the hydration process, which might require addition of retarders, decreasing the amount of cement, or addition of certain secondary cementitious materials (SCMs) (Gamil et al., 2019). On the contrary, a lower temperature slows down the hydration process and delays strength development (Ma et al., 2015). To counteract these effects, accelerators can be used in combination with, for example, rapid hardening cement and heat curing (Alhozaimy, 2009; Fang et al., 2018). Most standards limit the maximum concrete temperature to prevent cracking, lower strength, and delayed ettringite formation (Hale et al., 2005).

Digitalization of concrete temperature measurement is rather advanced (Wong et al., 2007; Norris et al., 2008; Barroca et al., 2013; Chen and Wu, 2015; Kim et al., 2015; Liu et al., 2017). State-of-the-art technologies with embedded sensors have been used. One common technology used to monitor the temperature is thermal imaging using infrared thermography. This technology is non-destructive, but it is applicable only to concrete not exposed to sunlight (Tran et al., 2017). Other techniques include, for example, fiber Bragg grating sensors, which are used to monitor temperature and shrinkage at the same time (Wong et al., 2007). Embedded nanotechnology/microelectromechanical systems (MEMS) sensors have been used to monitor moisture and temperature of concrete at the same time. Unfortunately, issues with repeatability and signal processing have been faced (Norris et al., 2008). Embedded thermal sensors have been used for temperature monitoring, but the thermography sensors must be in visual contact with the monitored concrete. It might be difficult to achieve due to, for example, form covers or other materials present on the concrete surface (Azenha et al., 2011). To overcome this drawback, automatic wireless sensors were used, but a 5 °C discrepancy was observed between actual and experimental values (Barroca et al., 2013). Another example is

TABLE 4 | Digital transformation of concrete temperature monitoring.

Parameters	Concrete type	Technology/method	Tool(s)	References
Shrinkage and temperature	Reactive powder concrete	Sensors	Fiber Bragg grating sensors	Wong et al. (2007)
Temperature and moisture monitoring	Normal concrete	Sensors	MEMS sensors	Norris et al. (2008)
Temperature	Normal concrete	Thermography	Embedded thermal sensors	Azenha et al. (2011)
Temperature and humidity	Normal concrete	Radio frequency integrated circuit (RFIC) and sensor technology	A Pt-100 resistance thermometer and RFIC transmitter	Chang and Hung (2012)
Temperature and humidity	Normal concrete	Automatic wireless sensor	Negative temperature coefficient (NTC) thermistor and an IRIS mote to create IEEE 802.15.4 network	Barroca et al. (2013)
Temperature	Normal concrete	Sensors	Passive wireless surface acoustic wave (SAW) sensor and orthogonal frequency coding (OFC)	Kim et al. (2015)
Temperature	Normal concrete	Sensors	A passive RFID sensor tag	Chen and Wu (2015)
Temperature	Normal concrete	Sensors	Embedded passive radio frequency identification (RFID) sensor tag	Liu et al. (2017)

TABLE 5 | Digital transformation of workability measurement in concrete.

Focused parameters	Concrete type	Method/technology	Tools	References(s)
Workability	SCC	ANNS	Linear regression	Bai (2003)
Slump	Fly ash and slag concrete (FSC)	ANNS	Simplex-centroid design	Yeh (2006a)
Slump and compressive strength	High strength concrete	ANN	MATLAB	Oztas (2006)
Modeling of slump loss	Normal concrete	ANNS	Root-mean-square (RMS) deviation	Yeh (2009)
Slump	Normal concrete	4D slump test using digital measurements and data processing with 3D depth sensor	Kinect sensor	Kim and Park (2018)
Slump flow, t50, yield stress, and plastic viscosity	SCC	Automated measurements	4C-rheometer	Danish Technological Institute and C.C (2020)

the so-called passive wireless surface acoustic wave (SAW) sensor combined with orthogonal frequency coding (OFC). The main constraints were related to the effect of propagation loss and isotropic radiation loss (Kim et al., 2015). Sensors utilizing passive radio frequency identification (RFID) and radio frequency integrated circuit (RFIC) (Chen and Wu, 2015; Liu et al., 2017) enabled short-range remote sensing and achieved the detection resolution of 0.25 °C (Chen and Wu, 2015; Liu et al., 2017). Their main shortcoming was the signal instability and a lack of electronic protection (Chang and Hung, 2012). A summary of methods and tool for digitalization of concrete temperature monitoring is given in **Table 4**.

Workability

Workability is an essential technological property of concrete controlling the casting process and affecting the quality of produced concrete elements or structures. It can be measured, for example, by slump or slump flow combined with T50 time in the case of self-compacting concrete (Fares, 2015). A number of digitalizing solutions have been introduced, and artificial neural networks (ANNs) is one the examples (Bai, 2003; Yeh, 2006a; Oztas, 2006; Yeh, 2009; Kim and Park, 2018). They produce a more accurate prediction of workability than the non-linear regression analysis (Yeh, 2006a), and it has the ability to model the slump for any mix design (Yeh, 2009). Another example method is based on 3D depth sensors (Kim and Park, 2018). Rheological properties of concrete described by the yield stress and the plastic viscosity are crucial for designing self-compacting concrete mixes (Wallevik, 2003; Roussel, 2011) (Ferraris et al., 2012). An effective device called 4C-Rheometer was developed by the Danish Technological Institute (Danish Technological Institute and C.C, 2020). It enabled to determine rheology based on automated measurements of slump flow and flow time. A summary of digitalization of workability measurements is given in **Table 5**.

Setting Time and Hydration Rate

Initial and final setting times of cement are used to monitor the hardening rate. The initial setting time indicates how long concrete mix maintains its plasticity. It indicates the allowable time to cast the concrete. The final setting time indicates the time after which concrete loses its plasticity, and it is especially useful for planning surface finishing processes. Both times are related to the hydration process, which can be monitored using calorimetry and measuring

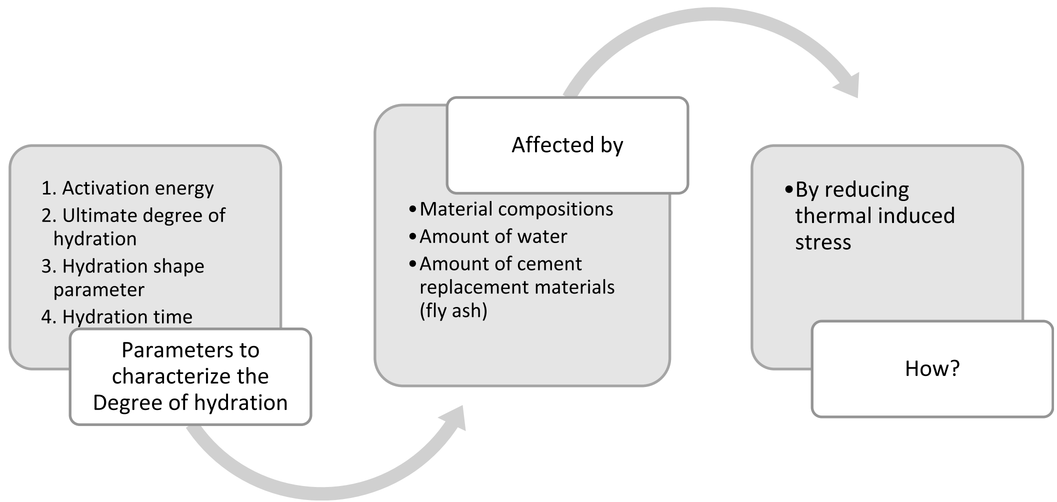

FIGURE 1 | Parameters and process used to characterize cement hydration (summarized from the work of Xu et al., 2010).

the evolved heat (Mostafa and Brown, 2005; Xu, 2011; Gawlicki et al., 2010). Parameters affecting the degree of cement hydration are summarized in **Figure 1** (Xu et al., 2010).

Several attempts were made to digitalize the assessment of the setting time. For example, Rizzo et al. (2014) used a non-destructive setup measuring strength development by sensors detecting the propagation of highly non-linear solitary waves (HNSWs). The waves were reflected at the sensor interface and transmitted to the monitored concrete. The transmission time and the reflection from the interface were measured and compared with the hydration time. These parameters were then correlated with initial and final setting times measured by using the Vicat apparatus. The hydration rate has been also monitored using the Fabry–Perot fiber optic temperature sensor. The concrete temperature depended on the water-to-cement ratio (Zou et al., 2012). Yet another effective method to digitalize the hydration rate is the monitoring of the crack formation (Yang et al., 2010). The hydration degree was also assessed by the thermogravimetric analysis (Debouchа et al., 2017). The method estimated the ultimate amount of bound water, which was verified by isothermal calorimetry combined with the assessment of compressive strength. The differential thermal and thermogravimetric analysis was also used to estimate the degree of hydration. In that case, the degree of hydration was calculated using experimental results. A good agreement between results based on differential thermal and thermogravimetric analysis was observed (Monteagudo et al., 2014).

The hydration process can also be measured using other methods, including X-ray diffraction (XRD), scanning electron microscopy (SEM), thermogravimetric analysis (TGA), or non-contact impedance measurement (NCIM) (Tang et al., 2016). For example, XRD was combined with calorimetry to monitor the hydration of cement blended with fly ash for the first 44 h. It enabled estimating the effects of fly ash (FA) (Dittrich et al., 2014).

Concrete Maturity

Maturity is an indicator used to predict strength development depending on the curing temperature (Chengju, 1989; McCullough and Rasmussen, 1999; Topçu and Toprak, 2005; Zhang et al., 2008; Yikici and Chen, 2015). The required (Ballim and Graham, 2009; Lee and Hover, 2015) systems based on that concept have been developed. For example, high-performance concrete paving (HIPERPAV) software utilized temperature data and the maturity concept to estimate the concrete strength at an early age (Ruiz, 2001). Another system developed by Giatec Scientific Inc.is based on wireless temperature sensors integrated with a special smartphone application. It enables live monitoring, but the maximum allowable distance between the sensor and the monitored concrete surface is limited (De Carufel, 2018).

Mechanical Properties

The compressive strength of concrete is certainly the most commonly used indicator of mechanical properties (Damineli et al., 2010; Yang et al., 2010; Ma et al., 2015). It is usually determined using a cube compression test, which is a time-consuming process. Consequently, several models have been created to reliably predict the strength without the need of physical testing. The ANNs method, described earlier, has been used in several studies (Lee, 2003; Kim et al., 2004; Yeh, 2006b; Prasad et al., 2009). It could estimate the compressive strength taking into account slump, air content, and fly ash amount as indicators in PreConS (intelligent system of strength). Unfortunately, the system showed a lower reliability at variable curing temperatures (Lee, 2003). Others used the ANN approach but based on different concrete mix proportions (Kim et al., 2004). In that case, literature data were used to estimate the compressive strength of SCC and high-performance concrete (HPC) taking into account the volume of fly ash and the water-to-cement ratio (Prasad et al., 2009). ANNs were also combined with the image processing technique and design of

TABLE 6 | Digital transformation of the compressive strength of concrete.

Focused mix design component	Method	Technology	Concrete type	References
Varying slump, air content, and fly ash	Laboratory test and computational analysis using ANNS	ANNS	Non-conventional concrete	Lee (2003)
Different sets of concrete mix proportions	Laboratory test and computational analysis using ANNs	ANNS	Conventional concrete	Kim et al. (2004)
Two different concrete mixtures M20 and M30	Non-destructive testing	Ultrasonic pulse velocity (UPV) and ANNS	Conventional concrete	Kewalramani and Gupta (2006)
Fly ash replacement by 0–50% and the effect on strength	Laboratory test and analysis using ANNS	Design of experiments and ANNS	Non-conventional concrete	Yeh (2006b)
Mix proportions	Analytical study of existing historical data	Adaptive network–fuzzy inferencing system	Conventional concrete	Tesfamariam and Najjaran (2007)
High-volume fly ash and water-to-cement ratio	Computational analysis using ANNs and data from the literature	ANNS	SCC and high-performance concrete (HPC)	Prasad et al. (2009)
Early-age concrete strength	Electromechanical impedance measuring chip and piezoelectric transducer installed in a Teflon-based	Active wireless sensing system	Normal concrete	Providakis et al. (2011)
Different concrete classes with different w/c ratios	Laboratory analysis of samples	Image processing (IP) technique	Conventional concrete	Basyigit et al. (2012)
w/c ratio, curing, amount of cement, compression, and additive	Non-destructive testing	ANNS and IP	Non-conventional concrete	Dogan et al. (2017)
w/c ratio and the recycled aggregate replacement percentage	Laboratory analysis of samples and analytical model development	Convolutional neural network with deep learning using softmax regression	Non-conventional concrete	Deng et al. (2018)
w/c ratio, water absorption, fine aggregate, natural coarse aggregate, recycled coarse aggregate, water-to-total material ratio	Analytical study of existing historical data	ANN	Environmentally friendly concrete	Naderpour et al. (2018)
Mix proportions	Experimental data	ANN with a modified firefly algorithm (MFA)	High-performance concrete	Bui et al. (2018)
Cement content, oven dry density, water-to-binder ratio, and foamed volume	An experimental database and historical data from the literature	Extreme learning machine model	Lightweight foamed concrete	Yaseen et al. (2018)
Ultrasonic wave propagation and concrete maturity	Non-destructive tests	Smart temperature (SmartRock) and PZT (piezoelectric) sensors	Non-conventional concrete	Tareen et al. (2019)
Cement replacement with fly ash and silica fume	Samples were crushed, and images were taken by using a DSLR camera	ANNS and IP	Non-conventional concrete	Waris et al. (2020)
Early age Compressive strength	Internet of Things (IoT)	Temperature sensors and Wi-Fi microcontrollers	Conventional concrete	John et al. (2020)
Impact of fly ash admixture	Machine learning algorithms	Genetic engineering programming and ANNs	Self-compacting concrete	Song et al. (2021)
Mix design	Machine learning	Hyperparameter tuning	High-performance concrete (HPC)	Nguyen et al. (2021)

experiments to estimate the strength (Dogan et al., 2017; Waris et al., 2020). It enabled prediction of various mechanical properties, including compressive strength, modulus of elasticity, and maximum deformation, reaching 98.65% accuracy. ANNs were also efficiently incorporated in an approach based on utilizing data obtained from ultrasonic pulse velocity (UPV) measurements (Kewalramani and Gupta, 2006). Similarly, a neural expert system was used to predict the strength based on results from testing a total of 864 concrete specimens. The applied ANN model used a back-propagation learning algorithm, and the results were compared to a built-in expert system, which enabled prediction of the strength using rule-based knowledge representation techniques (Gupta et al., 2006). Both compressive and tensile strength of high-performance concrete were determined using a modified firefly algorithm–artificial neural network expert system. A good correlation between actual and predicted results was achieved (Bui et al., 2018).

A deep learning prediction method has been applied to predict the compressive strength of recycled aggregate concrete. The model used the water-to-cement ratio and the recycled aggregate replacement percentage as input parameters. Tests were performed on 74 concrete blocks. The achieved precision was higher than that of a traditional neural network (Deng et al., 2018). A machine learning approach has been utilized to predict the compressive strength at different ages for concrete with high fly ash content. The water cycle algorithm and the genetic algorithm showed a good correlation between the variation of fly ash content and compressive strength (Naseri, 2020).

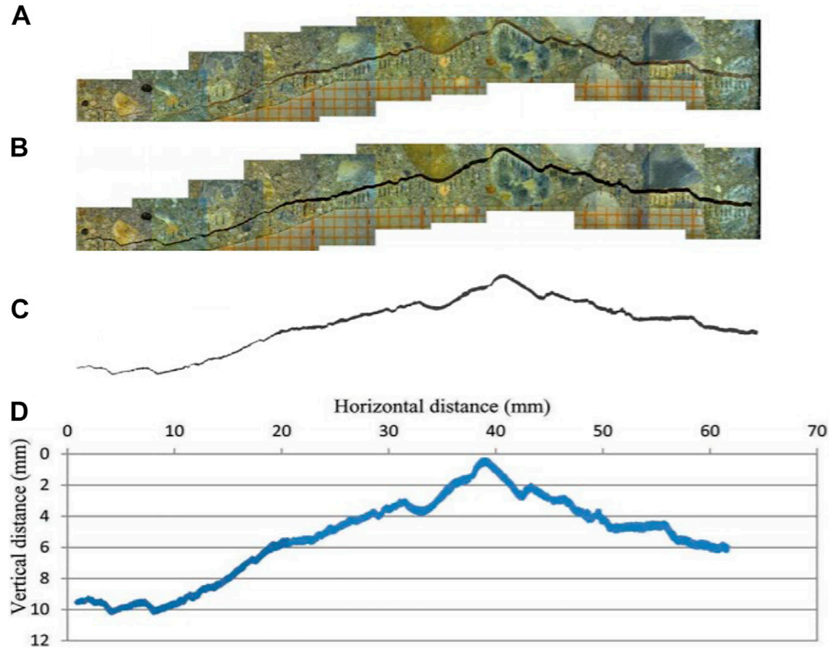

FIGURE 2 | Example of crack width measurement using digital image processing (Nagy, 2014).

Real-time prediction of the compressive strength has been carried out using data obtained using novel types of sensors (Providakis et al., 2011; Tareen et al., 2019; John et al., 2020). The early-age concrete strength was effectively estimated using data obtained from the active wireless sensing system (John et al., 2020). It used an electromechanical impedance measuring chip and a piezoelectric transducer installed in a Teflon-based (Providakis et al., 2011). Other approaches to predict the early strength used smart temperature (SmartRock) and PZT (piezoelectric) sensors with ultrasonic wave propagation combined with the concrete maturity concept (Tareen et al., 2019). Recently, the technology of Internet of things (IoT) was utilized to estimate the compressive strength using temperature sensors and Wi-Fi microcontrollers. The technology enabled real-time monitoring of strength (John et al., 2020). A summary of digitalization methods for prediction of compressive strength is shown in **Table 6**.

CRACK MONITORING

Crack monitoring remains a major concern in the concrete industry, and it is crucial for safety and maintenance costs (Omondi et al., 2016). Concrete cracks are caused by two effects, that is, extrinsic and intrinsic (Li et al., 2018a). The former is induced by the application of excessive loads. The intrinsic effects are related to the hardening process and are considered as non-structural. Intrinsic cracks are controlled by the mix design, mixing method, ambient temperature, and humidity (Bolleni, 2009). Automated crack detection and monitoring are still in the developmental stage, and various approaches have been considered. Digital image processing is certainly one of the most used methods (Dare et al., 2002; Chen et al., 2006; Nagy, 2014; Gehri et al., 2020). An automated image processing technique with multitemporal crack measurements detected the extrinsic cracks in concrete. The automatic method accurately delineated cracks even when using poor-quality images (Dare et al., 2002). The same method was applied to study the relationship between the crack width and its expansion with multitemporal image processing. In that case, images were taken every 2 weeks with a high-resolution scanner. The method enabled automatic crack tracing and showed a good correlation between the estimated width and the manual measurement (Chen et al., 2006). Crack width was also measured by two emerging technologies, that is, the image digitalizing method and the digital image processing (DIP) method combined with a digital microscope that enabled mapping the tortuosity of cracks (Nagy, 2014). An example process of transforming crack monitoring data into a digital form is shown in **Figure 2**. The process starts by taking an image of the crack followed by adjustment and cropping of the crack line. In the next step, pixel coordinates are used to determine the crack width (Nagy, 2014).

The same technology has been used to monitor the crack behavior and the crack orientation by extracting images with the digital image correlation (DIC) method (Gehri et al., 2020). The obtained results were limited only to closely spaced cracks. DIC has been also used to study the fracture behavior of concrete interfaces (Shah and Chandra Kishen, 2011). The used optical and non-contact measurement tool analyzed the displacement of the surface using images obtained before and

TABLE 7 | Concrete crack monitoring using digital technology.

Targeted properties	Type of cracks	Technology/method	Tool(s)	References
Crack detection	Extrinsic	Automated image processing techniques using multitemporal crack measurements	Automatic crack detection and algorithms (the route finder and the fly fisher)	Dare et al. (2002)
The relationship between the crack width and its expansion	Extrinsic and intrinsic	Multitemporal image processing where photos are taken every 2 weeks. A high-resolution scanner AGFA DUOSCAN T2500 was used to scan the digital images	Automatic crack tracing using Using an analog camera (Rolleiflex 6008 Integral) and film (Kodak Ektachrome 64)	Chen et al. (2006)
Crack width and length	Extrinsic	Digital camera embedded to a calibrated cylindrical attachment	Digitales Rissmess-System and a digital crack monitoring system	Dare et al. (2002)
Defect detection	Extrinsic and intrinsic	Thermography	Thermal imaging/infrared thermography (IRT)	Bolleni (2009)
Fracture property of concrete interfaces	Extrinsic	Digital image processing	Correlation technique	Shah and Chandra Kishen (2011)
Crack width	Extrinsic	Image digitalizing and digital image processing (DIP) methods	Digital microscope and digital image processing	Nagy (2014)
Crack detection and orientation	Extrinsic and intrinsic	Combined acoustic emission (ear) and digital image, Correlation techniques (eye)	Digital image correlation	Omondi et al. (2016)
Monitoring autogenous crack healing	Intrinsic	Non-destructive monitoring	Near-field microwave reflectometry, X-ray diffraction, and scanning electron microscopy	Mehdipour et al. (2018)
Crack detection	Extrinsic	Local binarization algorithm	Gray-scale images	Li et al. (2018b)
Microcrack detections	Intrinsic	Ultrasound-excited thermography	Thermal imager	Jia et al. (2019)
Crack behavior and orientation	Extrinsic and intrinsic	Extraction using an image processing method	Digital image correlation (DIC)	Gehri et al. (2020)
Crack spacing prediction of fiber-reinforced concrete	Extrinsic and intrinsic	Machine learning models	Multilayer perceptron (MLP) neural network and an adaptive neuro-fuzzy inference system	Rezaiee-Pajand et al. (2021)

after the displacement occurred. Another application of DIC has been monitoring and measuring deformation developing in compression (Choi and Shah, 1997). Results showed a well-balanced image rate for both lateral and axial deformation after the peak load.

More advanced methods were applied to determine the crack width and length using a digital camera embedded in a calibrated cylindrical attachment. The crack width could be estimated reliably, but the obtained results strongly depended on the operator (Dare et al., 2002).

Other new technologies that have been used to detect and monitor cracking of concrete include thermography (Bolleni, 2009), combined acoustic emission and digital image correlation techniques (Omondi et al., 2016), local binarization algorithm (Li et al., 2018b), and ultrasound-excited thermography (Jia et al., 2019). Thermography uses a thermal camera based on the infrared radiation, and it does not require a direct access to concrete layers to detect the damage (Bolleni, 2009). This method has also been combined with the ultrasound-excited thermography and enabled detection of microcracks having width between 0.01 and 0.09 mm (Jia et al., 2019). DIC has been successfully combined with acoustic emission technology to detect cracks and determine their orientation (Omondi et al., 2016). Yet another tested approach is a technology based on a local binarization. The color of the image is transferred into a binary image that has two colors, typically black and white. The image is then processed to detect the surface and cross-sectional area of present cracks (Li et al., 2018b). A summary of digitalization of crack formation in concrete is shown in **Table 7**.

DISCUSSION

More pieces of information were involved in the production of concrete, such as raw material characterizations, mix design, and properties of ready concrete, which are essential parameters used to envisage the quality of the end-product. Mostly, this information is acquitted manually in the laboratory. This process is time consuming, and technical experts need time to make quick judgments about modifying the mix design or developing the mix for specific use and environment condition. To save time and produce favorable and good-quality concrete, transforming information acquisition to real-time updates using digital technologies is preferred. The possibility of digital transformation of these essentials seems to be valid and possible; perhaps, more integration of different technologies can work efficiently to develop a system to obtain and communicate concrete information. The information needed from the source of raw materials at the quarry sites and the cement production plant by the engineer who develops the mix is surface area, specific gravity, shape, gradation, etc. Having this information on time will allow the mix design developer to adjust the proportions for the specific needs. Then, during the casting process, engineers need to monitor the concrete temperature, workability, formwork pressure, which is not discussed in this article, casting rate, maturity of the concrete to decide on the formwork removal time, mechanical properties, and

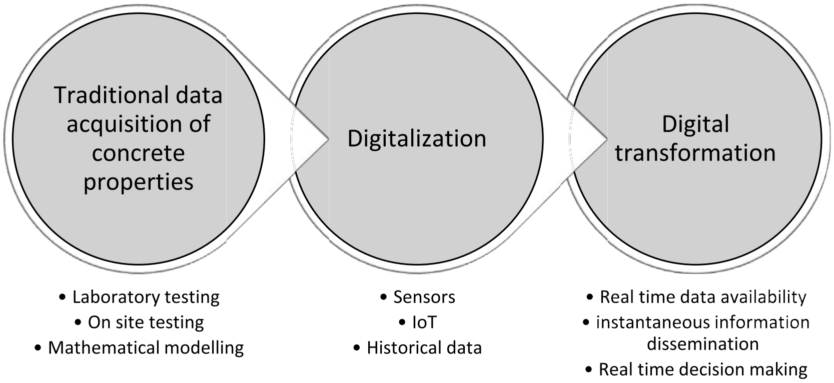

FIGURE 3 | Digital transformation of concrete properties.

crack monitoring. The question comes about merging all this information in one complete system using emerged technologies with embedded sensors and IoT for instantaneous communication, **Figure 3**. Extensive research has been carried out, as discussed in this article, to gradually transform the data acquisition into a digital form. Still, not all the attempts have been applied at the jobsite. There are reasons and challenges for low acceptance, and the process involves consideration of a multitude of stages. The first is the availability and accessibility of technology. Then, the question comes about the acceptance and confidence from the side of construction stakeholders of the technology, and that incurs some cost and expertise; these restrains need to be addressed through intensive research and full-scale experiments. It is suggested for future development to integrate the current technologies and applications into one integrated system for possible information acquisitions and instant communication.

CONCLUSION

Digitalization can be defined as converting information into a digital format and using these data to control, for example, the production and usage of concrete. Digital transformation enables us to save time and cost, facilitates access to information, and increases efficiency and readiness. In the concrete industry, the digital transformation of concrete properties and production helps to create a more consistent and faster construction process. Availability of real-time data enables engineers to follow and control the entire production process more efficiently and with higher reliability. Access to data is facilitated by, for example, cloud storage platforms. For example, the construction process can be accelerated and made safer by more accurate prediction of the formwork removal timing. In the current era, more advanced digital concrete has been introduced, and that technology needs to be coupled with the digitalized process of concrete data acquisition.

The real-time data assist engineers and managers in the decision-making process. The decision can be related, for example, to optimizing the mix design by reducing the usage of raw materials, thus leading to enhanced sustainability. On the negative side, the digital transformation, in the case of concrete technology, is a complex process due to not yet fully understood basic processes controlling, for example, hydration of Portland cement. An even worse situation is faced in the case of new ecological binders. Only for these reasons, it is extremely difficult to develop reliable models. Models which could be used to design concrete mixes predict strength development, crack formation, or deterioration due to various types of exposures. Another set of problems is related to the acceptance of the concrete and construction industry as well as compliance with current regulations and standards. There is also a need to ensure that the acquired data are communicated and stored correctly, analyzed, and interpreted by the responsible personnel. Other challenges include proper installation of sensors, data collection and storage devices, and data safety or data transmission.

There is still a significant amount of work to be completed before benefits of digitalization could be fully utilized in concrete technology. Problems to be solved are related not only to basic phenomena, for example, hydration of cement, but also to full-scale real-life applications with a number of factors not being present in laboratory settings.

AUTHOR CONTRIBUTIONS

YG has established the concept of the article, collected and analyze the data while AC has reviewed and supervise the work. He also contributed to proofreading and revising the article critically for important intellectual content.

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